Received: 24 January 2023 | Revised: 21 August 2023 | Accepted: 8 September 2023

DOI: 10.1002/ecs2.4737

ECOSPHERE
AN ESA OPEN ACCESS JOURNAL

ARTICLE

Climate Ecology

The predictability of near-term forest biomass change in boreal North America

Arden L. Burrell[1] | **Sol Cooperdock**[2] | **Stefano Potter**[1] | **Logan T. Berner**[3] | **Robert Hember**[4] | **Matthew J. Macander**[5] | **Xanthe J. Walker**[3,6] | **Richard Massey**[3] | **Adrianna C. Foster**[7] | **Michelle C. Mack**[6] | **Scott J. Goetz**[3] | **Brendan Rogers**[1]

[1]Woodwell Climate Research Center, Falmouth, Massachusetts, USA

[2]Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, California, USA

[3]School of Informatics, Computing, and Cyber Systems, Northern Arizona University, Flagstaff, Arizona, USA

[4]Forest Carbon and Climate Services, Ministry of Forests, Government of British Columbia, Victoria, British Columbia, Canada

[5]ABR, Inc.—Environmental Research & Services, Fairbanks, Alaska, USA

[6]Center for Ecosystem Science and Society, Department of Biological Sciences, Northern Arizona University, Flagstaff, Arizona, USA

[7]National Center for Atmospheric Research, Boulder, Colorado, USA

Correspondence
Arden L. Burrell
Email: aburrell@woodwellclimate.org

Funding information
National Aeronautics and Space Administration (NASA), Grant/Award Numbers: 80NSSC19M01, NNX17AE44G; NVIDA; Strategic Environmental Research And Development Program (SERDP), Grant/Award Number: RC18-1183

Handling Editor: Charles D. Canham

Abstract

Climate change is driving substantial changes in North American boreal forests, including changes in productivity, mortality, recruitment, and biomass. Despite the importance for carbon budgets and informing management decisions, there is a lack of near-term (5–30 year) forecasts of expected changes in aboveground biomass (AGB). In this study, we forecast AGB changes across the North American boreal forest using machine learning, repeat measurements from 25,000 forest inventory sites, and gridded geospatial datasets. We find that AGB change can be predicted up to 30 years into the future, and that training on sites across the entire domain allows accurate predictions even in regions with only a small amount of existing field data. While predicting AGB loss is less skillful than gains, using a multi-model ensemble can improve the accuracy in detecting change direction to >90% for observed increases, and up to 70% for observed losses. Higher stem density, winter temperatures, and the presence of temperate tree species in forest plots were positively associated with AGB change, whereas greater initial biomass, continentality (difference between mean summer and winter temperatures), prevalence of black spruce (*Picea mariana*), summer precipitation, and early warning metrics from long-term remote sensing time series were negatively associated with AGB change. Across the domain, we predict nondisturbance-induced declines in AGB at 23% of sites by 2030. The approach developed here can be used to estimate near-future forest biomass in boreal North America and inform relevant management decisions. Our study also highlights the power of machine learning multi-model ensembles when trained on a large volume of forest inventory plots, which could be applied to other regions with adequate plot density and spatial coverage.

KEYWORDS
biomass change, boreal forest, early warning signals, Extreme Gradient Boost, machine learning, North America

INTRODUCTION

The boreal forest is the second largest forest biome, accounting for roughly two thirds of global forest carbon stocks and one fifth of the global forest carbon sink (Bradshaw & Warkentin, 2015; Pan et al., 2011). The North American boreal forest is rapidly warming at a rate that exceeds the adaptive capacity of trees in some regions (Gauthier et al., 2015). Changes in aboveground biomass (AGB) reflect both the natural forest disturbance-recovery dynamic (Wang et al., 2021) as well as the ongoing impacts of climate change (Chen et al., 2016; Hember et al., 2017a; Sulla-Menashe et al., 2018). Despite the importance for predicting the impact of forests on the global carbon cycle and for informing management decisions, the effects of climate change on biomass in the boreal zone are not well understood (Chen et al., 2016; Wang et al., 2021). A growing number of studies identified processes such as droughts and wildfires that have the potential to reverse the boreal carbon sink as warming continues (Hember et al., 2017a; Walker et al., 2019). Well-planned management interventions informed by robust predictions of AGB change on a 5- to 30-year scale have the potential to help ameliorate this risk (Anderegg et al., 2020). However, forecasts informing decisions on this timescale are lacking, mainly because the current scientific modeling infrastructure is not designed to forecast AGB on a decadal timescale (Rogers et al., 2018) and, when available, resource manager-specific growth models typically lack climate change information (Di Lucca, 2019).

Climate change is having multifaceted and potentially counteracting impacts on AGB in the boreal forest. In recent decades, climate change has positively influenced boreal AGB through increases in the growing season length (Gauthier et al., 2015; Hember et al., 2017a), increased nitrogen availability (Trugman et al., 2016), and CO_2 fertilization (Bradshaw & Warkentin, 2015; Liu et al., 2015). Climate change has driven mixed and negative impacts on boreal forest AGB though shifts in moisture availability (D'Orangeville et al., 2018; Hember et al., 2017a; Luo et al., 2019) and more frequent and intense droughts (Itter et al., 2019; Rogers et al., 2018), as well as increasing frequency of disturbance events like fires (Abatzoglou et al., 2018; Hanes et al., 2018; Jia et al., 2019; Walker et al., 2019) and disease or pest outbreaks (Jia et al., 2019; Rogers et al., 2018). These processes interact with each other in complex ways (Burrell et al., 2021; Peng et al., 2011), and can have different impacts on mature and younger forests (Chen et al., 2016; Sun et al., 2021). The complexity of these interacting process and forest responses has generated considerable uncertainty in the current extent and drivers of change in boreal AGB (D'Orangeville et al., 2018; Girardin et al., 2016; Wang et al., 2021), and are likely to continue changing with further climate warming (Zhang et al., 2022).

The extent and drivers of boreal forest change are generally assessed using repeated site-level measurements (Baltzer et al., 2021; Chen et al., 2016; D'Orangeville et al., 2018; Girardin et al., 2016; Rogers et al., 2018), satellite measurements of vegetation indices (VIs) such as the normalized difference vegetation index (NDVI) (Guay et al., 2014; Sulla-Menashe et al., 2018; Wang & Friedl, 2019), or process-based modeling (Birch et al., 2021; Foster et al., 2019; Mekonnen et al., 2019; Trugman et al., 2016). Although the broad patterns of change are similar in that they show increases in AGB over recent decades (Hember et al., 2017a; Sulla-Menashe et al., 2018), the results of these different approaches diverge considerably when assessing the magnitude of different drivers (Guo et al., 2018; Sulla-Menashe et al., 2018). For example, recent studies have attributed the widespread greening of the boreal zone to rapid warming and CO_2 fertilization (ALRahahleh et al., 2018; Gauthier et al., 2015; Yang et al., 2018). By contrast, a recent study over Canada's forests found that the majority of changes were driven by the disturbance-recovery dynamic with the impact of climate changes outside of this dynamic being geographically limited and relatively small in magnitude (Sulla-Menashe et al., 2018).

There are also large uncertainties in projections of future AGB change in the boreal zone (D'Orangeville et al., 2018; Yang et al., 2018). Land surface models overwhelmingly predict large increases in biomass over the observed period and 21st century driven primarily by increases in temperature (Olsson et al., 2019; Wang et al., 2021). However, these models tend to overestimate the positive impact of climate change and CO_2 fertilization over the observed period (Kolby Smith et al., 2016; Wang et al., 2021; Yang et al., 2018), and the modeled response of mature forests to climate change diverges considerably from what has been observed (Jia et al., 2019). This is likely due to models having limited representation of fire dynamics (Sanderson & Fisher, 2020), permafrost (Burke et al., 2020), drought effects (D'Orangeville et al., 2018), species types (Anderegg et al., 2021), and tree mortality (Boussetta et al., 2013; Felton, 2021). They also tend to misrepresent the impact of warming on CO_2 uptake (Zhu et al., 2019) and fail to capture moisture-limiting impacts on GPP in the late summer (Liu et al., 2020; Zhang et al., 2020). These problems led a recent Intergovernmental Panel on Climate Change (IPCC) report to conclude "low confidence in the projections of global greening and browning trends" (Jia et al., 2019), and why current predictions of AGB change are unsuitable for most management applications (Rogers et al., 2018).

Near-term predictions of biomass change are important for understanding and quantifying boreal-climate change feedbacks, informing forest management decisions, and designing carbon offset projects (Anderegg et al., 2020). While it does vary between organizations, most make decisions on a 1- to 30-year timescale. The decisions made by these organizations influence fire management, harvest, replanting, and the preservation of primary forest. Even if we ignore the aforementioned issues with land surface models, much of the existing process-based modeling is focused on long-term changes at coarse spatial resolutions, which are not helpful for managers requiring near-future site-level predictions to inform management decisions (Rogers et al., 2018).

As a result of the growing need for near-term predictions of AGB change, some studies have attempted to inform management decisions by conducting site-level modeling using statistical and machine learning (ML) methods (Lidberg et al., 2020; Liu et al., 2018; Sun et al., 2021). Existing ML studies have two primary potential hurdles that have limited their widespread use for biomass change prediction. The first hurdle is data availability, with small training datasets from geographically confined regions limiting the general applicability of ML modeling. The second is the asymmetrical impact of the disturbance-recovery dynamic of boreal forests, with increases in biomass following predictable growth curves (Jarvis & Linder, 2000; Jonsson et al., 2020), while the drivers of loss are often multifaceted and stochastic (Boyd et al., 2019; Hember et al., 2017b; Rogers et al., 2018), which complicates predictions for any specific location at a specific time. However, recent studies have shown there are legacy effects and "resilience debts" that lead to nondisturbance-driven declines in AGB (Boyd et al., 2021; Hember et al., 2017b; Itter et al., 2019), and indicators of tree mortality-driven AGB loss can be detected in remotely sensed data as many as 25 years prior to the loss event (Rogers et al., 2018). These early warning signal (EWS) metrics raise the possibility that an ML modeling approach trained with a sufficiently large and diverse dataset may be able to predict nondisturbance-driven biomass loss.

The aim of this study was to develop a ML-based predictive modeling approach that can be used to predict site-level changes in AGB across boreal North America and to test the limits of this predictability. We first compiled an extensive database of permanent sample plot (PSP) forest inventory sites with repeat measurements collected by 13 different agencies across Canada and Alaska. We then trained ML models and used them to test several hypotheses: (1) performance of AGB change prediction will vary regionally depending on the number of PSP sites, (2) prediction accuracy decreases as the prediction window increases, (3) negative changes in AGB due to background mortality and partial disturbance can be predicted but with lower accuracy than gains, and (4) the direction of future AGB change will vary regionally depending on climatology and climate trends with declines in biomass likely to occur in the southern boreal in areas more sensitive to drought.

METHODS

The aim of our methodology is to apply ML to a large dataset of field sites with repeat biomass measurements to predict the change in AGB (ΔAGB) between T_0 and T_n. Our modeling approach only used information available at T_0, including both inventory-based metrics as well as gridded information on prior climate and ecosystem dynamics, as this allows the models to predict biomass changes into the future without the need to also project the driver and response variables simultaneously. An overview of the methodology used in this study is shown in Figure 1.

Site-level database

PSPs with repeat inventory measurements are invaluable for understanding long-term changes in boreal forests. We quantified temporal changes in stand attributes (e.g., AGB) using repeat inventory measurements at PSPs distributed across boreal North America. Specifically, we assembled a database consisting of 106,828 census measurements collected by 11 government agencies between 1926 and 2017 at 24,690 sites across boreal North America (Figure 2). While forest inventory monitoring is widespread in this domain, the characteristics of monitoring programs vary among research groups and government agencies. A regional breakdown of sites is included in Appendix S1: Figures S1 and S2. This represents one of the largest databases of this type ever assembled, and contains data on time-varying species composition, dbh, mortality, stem density, damage flags, disturbance history, and stand age.

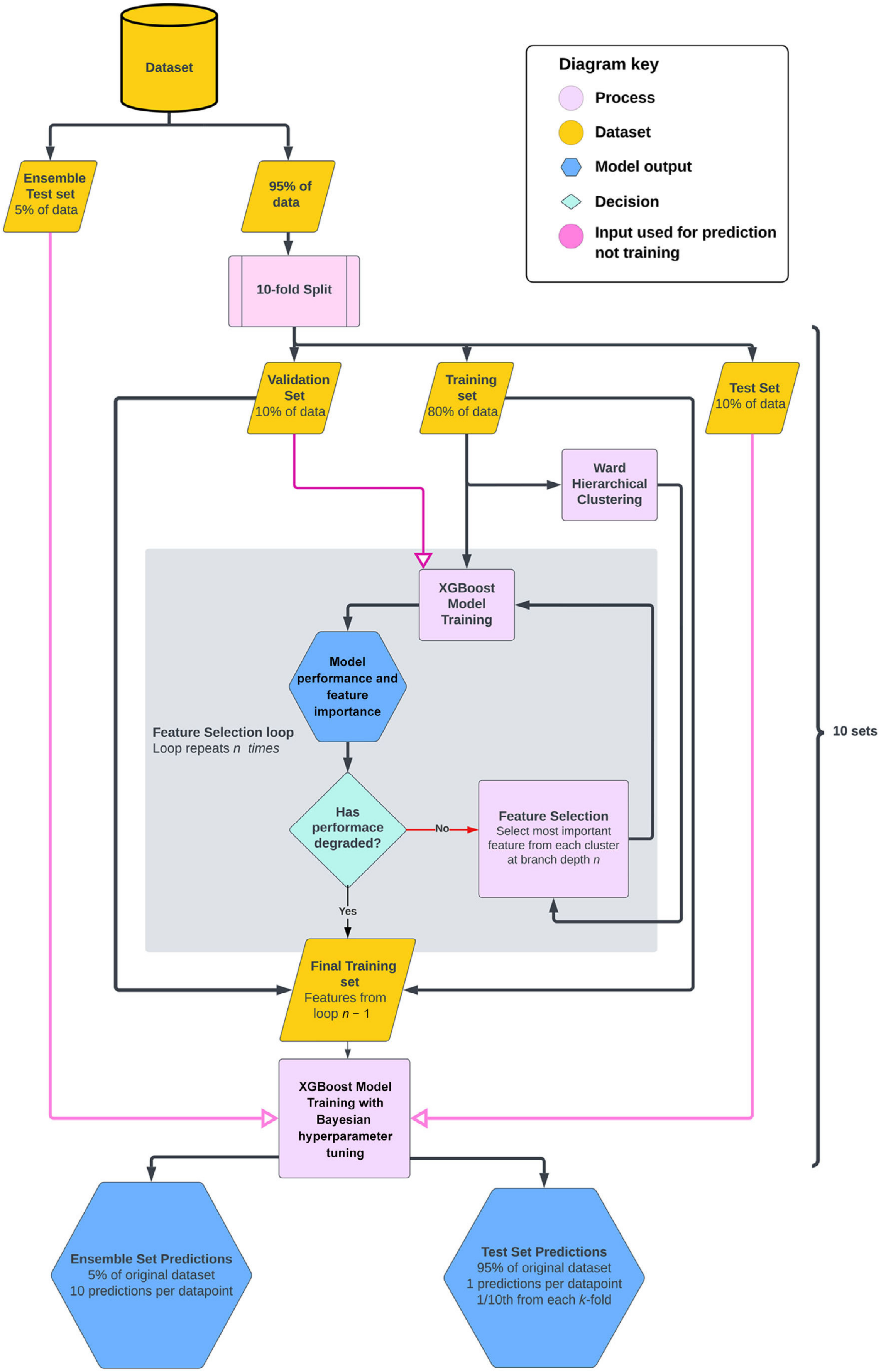

FIGURE 1 Flow diagram showing the construction of the dataset and the testing methodology.

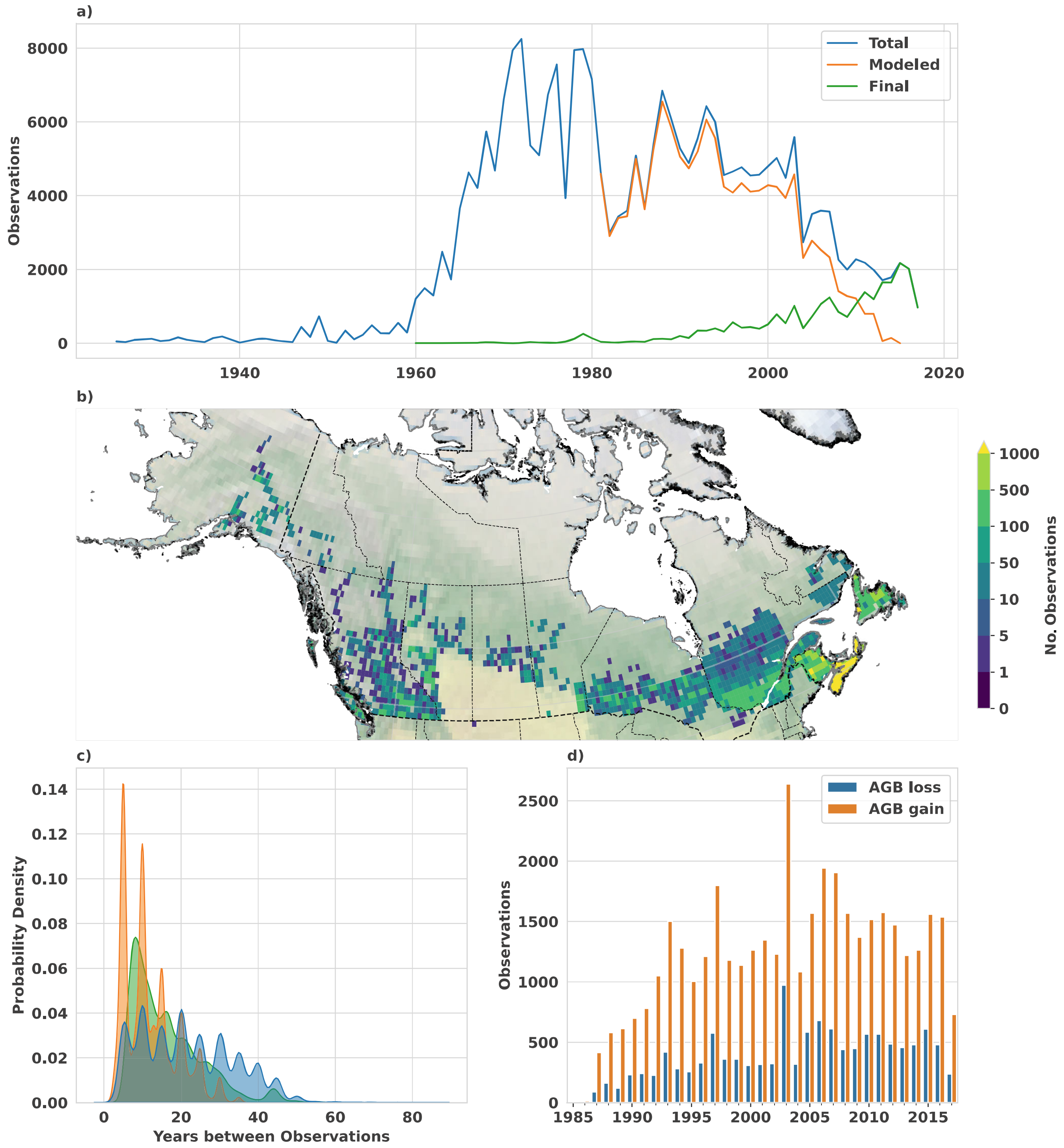

FIGURE 2 Characteristics of forest inventory site observation database. (a) The number of observations in the database. An observation is a field measurement at a site at a specific time. Modeled observations are those that were included in the XGBoost testing and training datasets, and final is the last observation at a given site. (b) Map of the number of modeled sites on a 1° × 1°-grid. Background image: Natural Earth Shaded Relief. (c) Probability density function of the gaps between observations. Colors match the classes in panel (a). For the final observation, it is the gap between the last observation and 2021. (d) The number of sites with biomass increases and decreases in the modeled dataset. AGB, aboveground biomass.

Differences in sampling methods through time and between agencies meant that not all parameters were available at every site, and raw observations were not always directly comparable. To account for differences in site dimensions, we converted all observations to an average per unit area basis (per hectare). We also standardized species information between four different species groupings (Appendix S1: Table S1). Both the counts of individual species and the grouped species types were included as predictor variables in our models. To allow for comparisons across sampling regions, we calculated stand-level AGB at every site for each census. This was done by calculating individual tree AGB using the Canadian national species-specific dbh-based tree AGB allometric equations (Ung et al., 2008) and then summing the AGB of all trees within each sample plot at each census. Allometric equations were available for most of the dominant tree species, but for some less common species, it was necessary to use generic "hardwood" or "softwood" equations unless there was a closely related species that could be substituted (e.g., *Larix laricina* for *Larix occidentalis*). Alaska-specific allometric equations (Alexander et al., 2012) were used for *Betula neoalaskana*, *Populus balsamifera*, *Picea glauca*, *Picea mariana*, *Betula kenaica*, *Picea lutzii*, and *Populus tremuloides*. The AGB from shrubs was not included because data about shrubs were not collected at many sites, and the overall fraction of AGB from them is expected to be low. This led to a total of four surveys and 72 species variables derived from site measurements.

Additional predictor variables

Recent changes in forest AGB were likely influenced by climate and soil characteristics, including the presence of permafrost. Therefore, we collected climate, soil, and permafrost as well as remotely sensed vegetation and disturbance data for every site. Disturbance data were included so that declines in forest AGB caused by stochastic disturbances such as wildfire, which are outside the scope of this study, could be excluded. We used the Alaskan Large Fire Database (Kasischke et al., 2002) and the Canadian National Fire Database (Stocks et al., 2002) fire history which, in combination with site records of disturbance, was used to exclude sites that were disturbed during training and prediction intervals.

For climate data, we used the ClimateNA product that is a locally downscaled historical climate dataset for North America (Wang et al., 2016). For every observation at each site, we calculated the mean, trend, and absolute trend on 21 climate variables (Appendix S1: Table S3). We used a 30-year window for climate metrics, which allowed us to account for decadal climate variability (Lloyd & Bunn, 2007). For soils, we used the SoilGrids 250m dataset (Hengl et al., 2017), and for permafrost, we used both the Northern Hemisphere permafrost map (Obu et al., 2019) and the Global Permafrost Zonation Index Map (Gruber, 2012).

Satellite time series measurements of VIs may help predict recent changes in forest AGB; for instance, EWS metrics derived from Landsat VIs have been used to detect tree mortality (Rogers et al., 2018). We therefore derived annual time series of summer VIs for each site using 30-m resolution measurements of surface reflectance from the Landsat satellites. Specifically, for a 90 × 90-m footprint centered on each site, we used Google Earth Engine (Gorelick et al., 2017) to extract all Landsat 5, 7, and 8 surface reflectance measurements made during July and August from 1984 to 2017. Following methods used in several recent studies, we identified high-quality, clear-sky measurements based on pixel and scene criteria, and then computed 10 VIs using clear-sky measurements (Appendix S1: Table S2). Because there are systematic differences in VIs among Landsat sensors, further cross-calibration is necessary to avoid spurious changes when generating VI time series from multiple sensors (Berner & Goetz, 2022; Sulla-Menashe et al., 2018). We therefore cross-calibrated the VIs among Landsat sensors using a recently developed ML technique that effectively minimized these biases (Berner et al., 2020; Berner & Goetz, 2022). For each VI at every site, we computed annual median summer values and then calculated the Theil–Sen slope (Theil, 1950) through years, pulse, EWS (Carpenter & Brock, 2011; Dakos et al., 2012), and Drift Diffusion Jump (DDJ) metrics (Carpenter & Brock, 2011; Dakos et al., 2012) (Appendix S1: Table S2), similar to Rogers et al. (2018). A minimum window of 5 years and a maximum window of 10 years prior to a given inventory measurement was selected as a trade-off between improved model performance using longer windows versus large reductions in the number of available observations for model testing and training. This 10-year window prior to inventory measurement is also consistent with prior research (Itter et al., 2019; Rogers et al., 2018).

We included sample interval as a predictor variable because it varied between observations (Figure 1). The sample interval is defined as the difference in years between T_0 and T_n, where T_0 is the year a given PSP site was surveyed and T_n is the next observation year used for testing and training the models, or the desired year for predicting future biomass changes. For sites with more than two measurements, every combination of T_0 and T_n was used. We removed any sites where disturbance occurred between T_0 and T_n. For fires, we excluded sites using the Alaskan Large Fire Database and Canadian National Fire Database and for other disturbances, we used disturbance flags in the PSP databases. While all regions did record disturbance information, many areas were missing information about the nature of the disturbance meaning it was not possible to consistently distinguish different disturbance causes (i.e., logging vs. insect outbreak). As such all sites flagged as disturbed were excluded. After removing data that failed the disturbance or missing data criteria, this gave a final training dataset of 916 possible predictor variables (most coming from different lengths of remote sensing time series before a given site observation) at every T_0 with 58,026 observation intervals across 17,124 sites.

Modeling changes in forest AGB

Our modeling approach aimed to predict the change in AGB (ΔAGB) between T_0 and T_n using site-level information on biomass and species composition, gridded information on climate, soil, and permafrost properties, and remotely sensed time series of VIs in the years up to and including T_0 (i.e., EWSs of mortality; Rogers et al., 2018). To do so, we used an Extreme Gradient Boosting regression algorithm as implemented in the Python XGBoost package (Chen & Guestrin, 2016). XGBoost was chosen because it is widely used, can tolerate missing data in the predictor variables, scales well in Cloud compute and GPU compute environments, and outperformed the more widely used Random Forest and Light Gradient Boosting Machine in both compute time and accuracy in our initial tests. While XGBoost is tolerant of missing data because it uses sparsity-aware split finding (Chen & Guestrin, 2016; Rusdah & Murfi, 2020), performance degrades as the amount of missing data increases. For this reason, sites with more than 50% missing data (mostly from VI time series) were excluded. This threshold was chosen to optimize the trade-off between increased model performance with more sites and decreased model performance due to missing predictors.

To ensure a completely independent test sample and prevent overfitting, we used a strict withholding procedure with a four-way split of the dataset combined with a *k*-fold rather than the standard two-way test/train set common in ML. The four sets included (1) a training set (train) used for training in both the feature and hyperparameter selection stages, and when training the final models; (2) the validation set ($\text{train}_{\text{val}}$) that acted as a withheld test set in the feature and hyperparameter selection stages, and then combined with the train set when training the final models; (3) model test (test_{mod}), which was a fully withheld set that was unique to each model; and (4) ensemble test (test_{ens}), which was 5% of the dataset fully withheld from all 10 models to assess the model ensemble performance. After the test_{ens} set was removed, a 10-way *k*-fold split was applied to the remaining dataset with 10% to test_{mod}, 10% to $\text{train}_{\text{val}}$, and 80% to the test set. The train and $\text{train}_{\text{val}}$ sets were used for the feature selection and model hyperparameter optimization (Xia et al., 2017; Yu & Zhu, 2020), and then combined with the training set for the final model. The model hyperparameters were set using Bayesian hyperparameter optimization. The procedure used to perform the splits, as well as the model feature and hyperparameter selection, is described in Figure 1 and Appendix S1.

The multiple subdivisions of the dataset and the strict grouping by sites at every split were implemented to ensure that test sets were fully withheld and there was no data leakage, which is a widespread problem in ML studies (Jones, 2019; Kaufman et al., 2012). The splitting and modeling of the dataset were then repeated using a more flexible set of criteria to assess the impact of including an earlier portion of the time series for a specific site on prediction performance. This approach is less strict because it allows the model to train and test on the same site, though at different parts of the time series. These two different groupings (site withholding ensemble, or SWE = withholding entire inventory sites, interval withholding ensemble, or IWE = withholding only particular measurement intervals within sites) allowed us to test model performance under different conditions, with the strict “site withholding” grouping giving model performance at completely unknown sites, and the less strict “interval withholding” grouping giving model performance at already established sites such as the existing PSPs.

Assessing model performance and predicting future change

To assess the model performance, we used R^2 score in the fully withheld test set, the median absolute error (MAE), and binned heatmaps of observed versus expected values. All statistical tests were performed using the scikit-learn Python package (Pedregosa et al., 2011). To examine the limits of performance, we also compared residuals grouped by factors like region, observed change direction, the temporal gap between observations, and differences between model ensembles. We also assessed intra-ensemble performance using the multi-model model mean and the proportion of models that agree on directionality in the test_{ens} set.

To assess the importance and impact of the different predictor variables, we used Shapley additive explanations (SHAP) (Lundberg & Lee, 2017). SHAP values represent how the model estimates of ΔAGB change depending on the value of the input features. The 0 point of the SHAP value is the default outcome of the model, which is the value the model predicts in the absence of any values in the predictors, also known as the model default or baseline output. Future predictions for 2020, 2025, 2030, and 2040 were performed by applying our final 10 models to the most recent observation at each site. Sites where the most recent observation was greater than 30 years from the prediction endpoint were excluded. This resulted in a database of 23,281 sites that can be used for future prediction. All maps show results from sites aggregated within a 1° × 1°-grid.

RESULTS

PSP database and the EWS signals

In total, our PSP database contained 24,690 sites and 106,828 total census measurements (mean of 4.3 observations per site). Of these, 17,124 sites with 58,026 observations had sufficient data to be included in model testing and training (Figure 2). There were large differences in the number of sites sampled across the 13 regions; for example, we were able to model 17,693 observations in Nova Scotia but only 209 in Saskatchewan. This disparity was also reflected in the number of measurements per site, with Alberta, British Columbia, and Saskatchewan all having an average of less than three measurements per site, compared with Manitoba and Nova Scotia where the average was greater than nine (Appendix S1: Figure S1). Increases in AGB were observed at 81% of measurement intervals, with the largest increases observed at sites with low initial biomass and in regions with the highest mean biomass (Appendix S1: Figure S1). The dominance of AGB increases compared with decreases was consistent across most regions, with increases varying from 66% in Saskatchewan and Quebec to >90% in British Columbia and Newfoundland.

Model performance and feature selection

Our 10-member ensemble of XGBoost models was able to predict changes in AGB with an ensemble R^2 of 0.46 in the fully withheld test sets (test_{ens}) for the SWE (withholding inventory sites entirely), and 0.62 for the IWE (withholding measurement intervals within sites) (Figure 3a,c). The less strict withholding procedure used by the IWE resulted in lower MAE (6.4 vs. 9.9 t ha^{-1}) and a better ability to predict the magnitude of AGB change, especially for biomass losses (Figure 2b,d). Figure 4b shows that the higher performance of the IWE reflects the models' ability to learn the sites, as the IWE error generally decreases with more site measurements. Overall, both ensembles were able to predict the direction of change correctly >82% of the time.

Both model ensembles showed similar behavior during feature selection with comparable total permutation importance placed on different feature groups (Figure 3a). Our feature selection approach reduced an initial 916 variables down to between 44 and 75 variables depending on the model without any loss in model performance. In total, 137 different variables were selected by at least one member of the two ensembles. When considered as a group, site-level inventory variables had the greatest permutation importance for both model ensembles (Figure 4a) and made up the three most important predictor variables (Figure 5; Appendix S1: Figure S5). We found the initial biomass at T_0 (biomass) was the most important predictor variable, followed by the observation gap (the gap in years between T_0 and T_n), continentality (the temperature difference [TD] between the hottest and coldest month), and initial stem density. Initial biomass at T_0 was negatively correlated with ΔAGB whereas both the observation gap and the initial stem density showed strong positive correlations (Figure 5). TD displayed a threshold effect where $\text{TD} > 30^\circ\text{C}$ has a negative effect and $<30^\circ\text{C}$ has a positive impact in the SHAP values (Appendix S1: Figure S6). The most important species variable was the fraction of black spruce (*P. mariana*), which had a negative correlation with ΔAGB. Similar variables were important for the subset of sites where the models predicted loss (Appendix S1: Figure S7). However, site variables such as observation gap and stem density were comparatively less important, and climate and EWS variables tended to be more important (Appendix S1: Figure S7).

Limits of model performance

We found residuals for both model ensembles showed no change in net bias (mean ≈ 0) as a function of observation gap, but the spread (99% CI) in the dataset grew as the gap between T_0 and T_n increased (Figure 6a,b). However, this pattern was largely because longer prediction windows include larger changes in AGB, and hence larger residuals; residuals normalized by (ΔT) did not show an increasing spread over time (Figure 6b; Appendix S1: Figure S9c,d). These relationships break down at approximately $\Delta T = 30$ years, either because there are relatively few measurements in the database that have a $\Delta T > 30$ (Figure 2c) or because this represents a limit for statistical extrapolation of AGB changes.

Models varied considerably in their ability to predict AGB gain versus loss. Overall, both ensembles were able to correctly predict change direction >82% of the time, but this may be biased by the fact that 81% of observations in the training data experienced AGB gains. Both

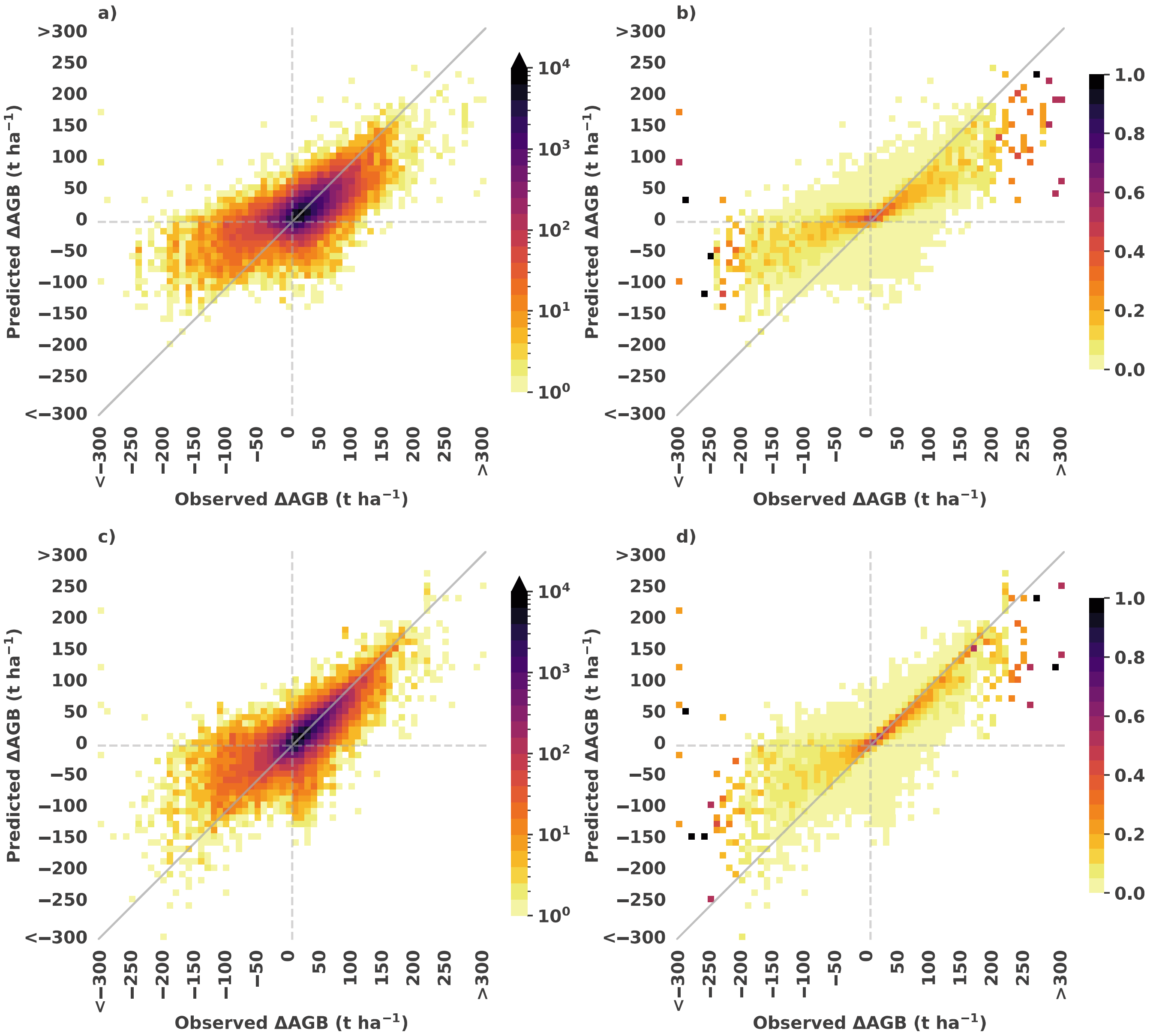

FIGURE 3 Model ensemble heatmaps: (a, b) heatmaps of the site withholding ensemble, (c, d) heatmaps of the interval withholding ensemble. (a, c) Binned heatmaps show the predicted versus observed values for the multi-model ensemble. (b, d) Heatmaps normalized for each observation bin show the observed versus predicted values for the multi-model ensemble. Each column of the normalized heatmaps sums to 1. AGB, aboveground biomass.

ensembles showed high accuracy when predicting biomass gains, with a 90.7% direction accuracy and residual of -6.4 t ha^{-1} for the SWE and 91.3% direction accuracy and residual of -4.2 t ha^{-1} for the IWE. The models did not perform as well at predicting declines in AGB (Figures 3b and 6a), with a significant net positive bias in the residuals (SWE: 26.3 t ha^{-1}, IWE: 17.2 t ha^{-1}) and a lower direction accuracy (SWE: 41.5%, IWE: 60.2%), although the IWE still performed better than the SWE. Differences in the frequency of both AGB loss and sampling intervals between regions mean there is a difference between the mean observation gap of measurements with ABG loss (12.0 years) versus gain (10.9 years), although this difference is too small to account for the disparity in model performance and does not explain differences in performance of loss and gain within the same region (Appendix S1: Figure S10).

The magnitude of the residuals varied considerably by region (Figure 6c; Appendix S1: Figure S10a,b). The largest MAE was in Quebec (17.1 t ha^{-1}), followed by British Columbia (11.5 t ha^{-1}), with all other regions falling between 5 and 10 t ha^{-1}. There were notable differences in the mean biomass at T_0 and the gap between observations (Appendix S1: Figure S1) with Quebec

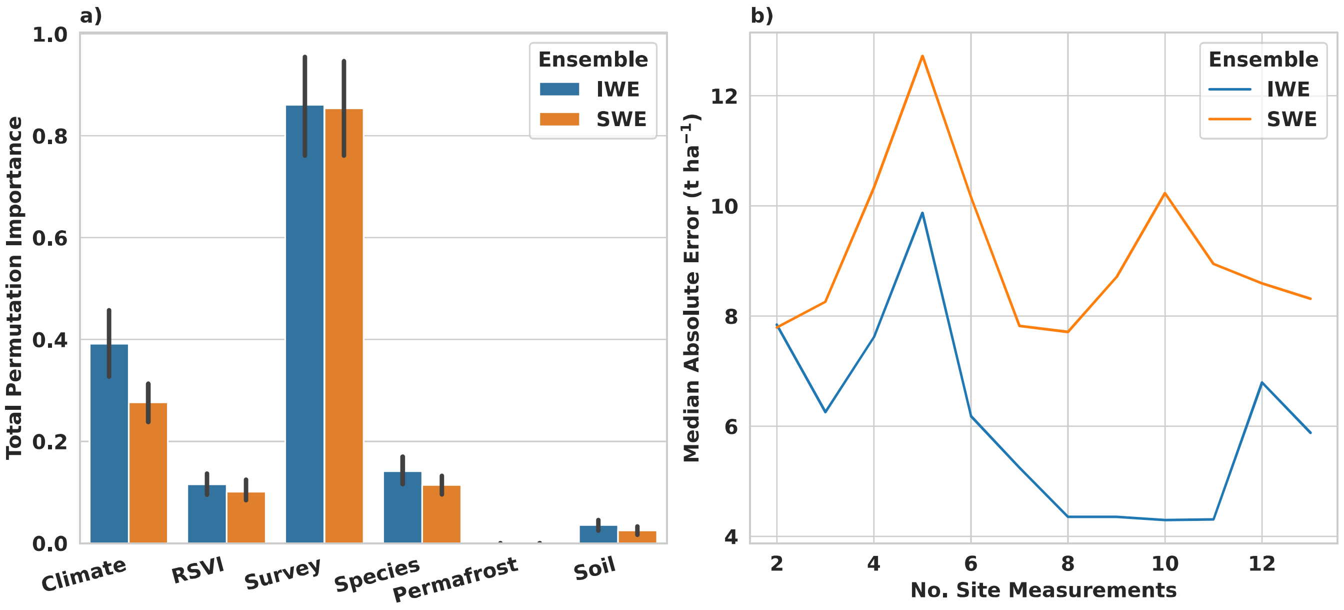

FIGURE 4 Model ensemble characteristics. (a) The summed model permutation importance scores for features grouped by data source. (b) The median absolute error of the two model ensembles (site withholding ensemble [SWE] and interval withholding ensemble [IWE]) grouped by the number of unique site measurements. RSVI, remotely sensed vegetation indices.

having a mean observation gap of 14.8 years compared to 7.9–11.6 for all other regions. As with the differences in residuals as a function of time, accounting for differences in initial biomass and observation gap mostly removed the difference in residuals between regions (Appendix S1: Figure S10c,d).

Model ensemble performance

To predict future biomass change, we used the multi-model ensemble that included 10 estimates at each location. To assess the ensemble performance, 5% of the dataset was fully withheld from all models (test$_{\text{ens}}$). For the SWE, the multi-model mean outperformed individual models with a MEA of 8.85 t ha^{-1} versus the individual models that had MAEs between 9.03 and 10.18 t ha^{-1}. The multi-model mean correctly identified the change direction observed 85% of the time, compared to 82%–84% for the individual models. The multi-model mean still underestimated AGB loss, correctly detecting loss in 39% of cases compared to 38%–44% for the individual models. Appendix S1: Figure S11a shows the agreement of the models regarding the direction of AGB changes. However, these accuracies are substantially improved by considering cases where all 10 ensemble models agreed on either AGB increases or decreases (Figure 7). In these instances, directional accuracy improved to >90% for AGB gains and 70% for AGB losses. In general, greater model ensemble agreement resulted in greater directional accuracy.

Future biomass predictions

The model ensembles predicted mostly gains in biomass at PSP sites across boreal North America over the coming decades (Figure 8; Appendix S1: Figure S12). Between the last site-level observation and 2020, the multi-model mean ΔAGB was positive at 76.9% of sites ($n = 18{,}051$) and negative at 23.1% of sites ($n = 5426$) with a mean observation gap of 13.3 years. Of the sites with predicted decreases in AGB, 2051 sites (38%) had all 10 members models predicted negative AGB change. Regionally, the most consistent increases were predicted to occur in Nova Scotia (95.2%) and Ontario (89.6%). Conversely, the most consistent decreases were predicted to occur in Alberta, where 70.7% of sites are predicted to decrease, as well as the Northwest Territories (63.6%) and Saskatchewan (63.3%). It should be noted that the Northwest Territories only had 22 sites that were used for prediction, which was 100 fewer than Yukon which had the second fewest. Looking further into the future, increases were predicted for 77.6% of sites in 2025, 77.2% in 2030, and 79.2% in 2040, with similar regional patterns as those observed for 2020. The reduction in areas with predicted biomass decreases is the result of a lack of recent sampling in regions with decline as opposed to changes in the direction of individual sites. Maps of predicted AGB changes and the number of sites, along

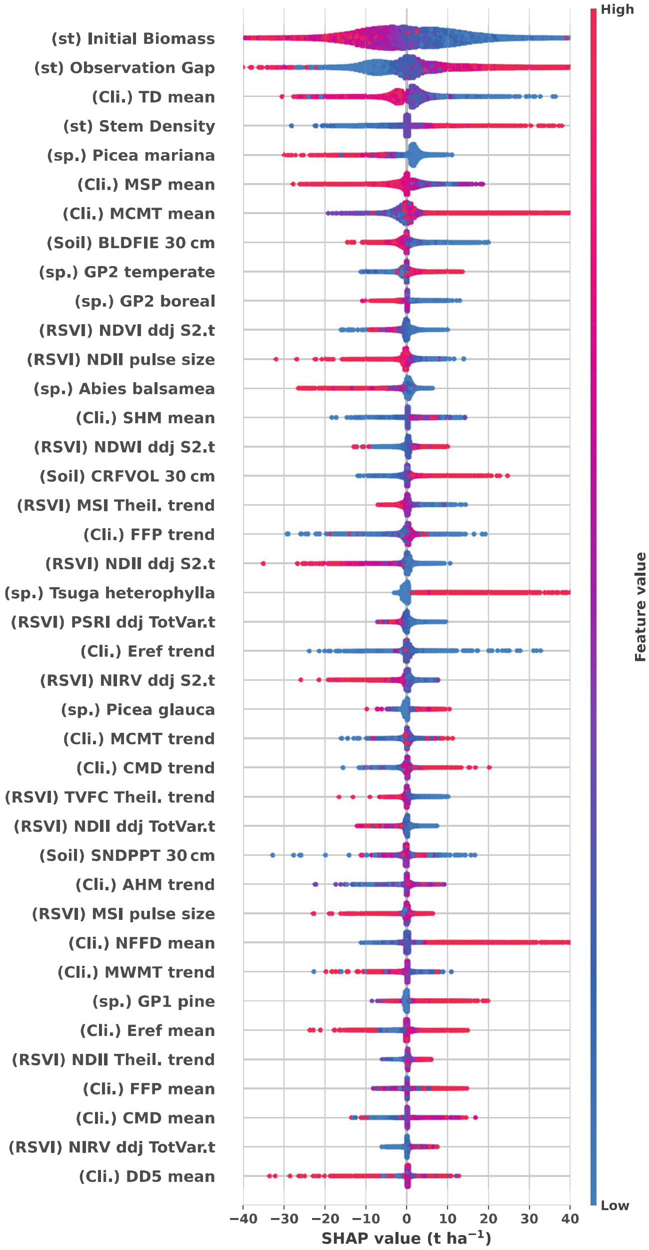

FIGURE 5 Aggregated Shapley additive explanation (SHAP) values for the 40 most important features for the site withholding ensemble models. Features are sorted from most to least important. A SHAP value of 0 represents the default outcome of the model, which for this model ensemble is a mean of ΔAGB 15.96 t ha^{-1}. The parentheses before the variable name indicate predictor type: site (st), climate (Cli), tree species (sp.), remotely sensed vegetation data (RSVI), and soil (soil). Full names of the predictors are found in Appendix S1: Tables S1–S4. The colors indicate the value of a feature within that predictors range, with blue indicating a low value and pink indicating a high value (e.g., Appendix S1: Figure S6). An example of what this looks like for an estimate at a single site is included in Appendix S1: Figure S8. AGB, aboveground biomass.

with versions for the EWS models, are included as Appendix S1: Figures S13–S17 and show very similar overall patterns between ensembles.

DISCUSSION

Modeling biomass change

Our modeling approach was able to robustly forecast changes in biomass at PSPs across boreal North America. We found AGB increased at 81.7% of sites in the PSP database, and our models predicted AGB to increase at 77% of sites between the last field observation and 2020 (assuming no extraneous disturbance). Widespread increases in AGB are broadly consistent with prior satellite observations showing extensive greening trends in boreal North America (Guay et al., 2014; Sulla-Menashe et al., 2018; Wang & Friedl, 2019). A single model is sufficient to detect the direction of change in 82%–84% of sites, and the agreement of our predictions with existing studies showing the spatial extent of greening shows that ML approaches can be used to predict AGB change.

Our first hypothesis was that model performance would vary regionally depending on the large differences in the availability of training data. Our results do not support this hypothesis and instead show that differences in model performance between regions can be explained by differences in sampling frequency (Appendix S1: Figure S10) and regional growth rates (Appendix S1: Figure S1d). This finding reinforces the usefulness of ML modeling for predicting AGB changes as it shows that data from a large spatial domain can partially address regional sampling gaps. There were significant regional differences in the frequency of loss observed in the PSP database (Appendix S1: Figure S1c), which ranged from <8% in Newfoundland and Labrador to >30% in Saskatchewan, Alberta, and Northwest Territories. There were also large differences in the regional availability of site data (Figure 2). For example, Saskatchewan had one of the highest loss rates (33%) but only 209 sites could be included in the model. Despite these differences, model performance was consistent between regions. The ability of our models to accurately predict biomass gains versus losses in areas with few site observations makes it valuable for addressing these large data gaps.

Our second hypothesis was that model performance would degrade as prediction interval increased. While true in absolute terms (Figure 6a), our ensembles showed no increase in the spread of normalized residuals as prediction interval increased, and only broke down at intervals of <3 years and >30 years (Figure 6b), which either represent the limits of predictability or the training dataset. Ensemble direction also showed no clear degradation in performance until the model approached the limits of the training dataset (Figure 6b,c). ML methods often perform poorly when trying to predict outside of range of the data used in training, an issue commonly referred to as the "area-of-applicability" or "extrapolation" problem (Colwell et al., 2012; Meyer & Pebesma, 2021). Our results also suggest this approach may still be limited by data availability rather than methodological or theoretical constraints.

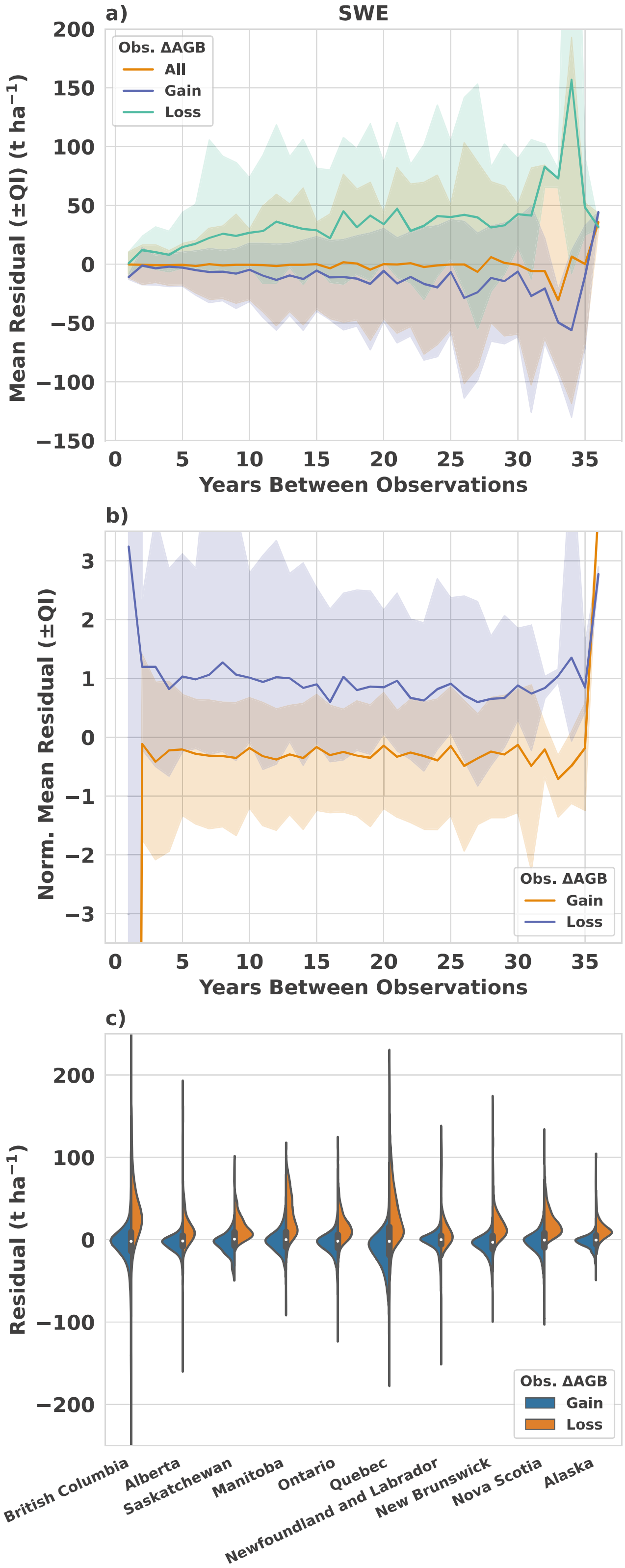

FIGURE 6 Site withholding ensemble (SWE) performance limits. (a) The mean and 99th percentile range (QI) of the residuals by years between observations (in tons per hectare). (b) The mean and 99th percentile range (QI) of the residuals by years between observations normalized by the mean absolute ΔAGB change per years between observations (in tons per hectare). (c) Violin plot of model residuals (in tons per hectare) by region. Blue shows observed AGB gain and orange shows observed AGB loss. Equivalent figures comparing the SWE to the interval withholding ensemble are included in Appendix S1: Figures S9 and S10. AGB, aboveground biomass.

Modeling biomass loss versus gain

Our third hypothesis was that losses in AGB would be harder to predict than gains in disturbance-dominated ecosystems such as the boreal forest (Sulla-Menashe et al., 2018; Wang et al., 2021). Increases in biomass were highly predictable with a directional accuracy of almost 91%, with model performance minimally degrading as prediction interval increased (Figure 6; Appendix S1: Figure S9). The excellent performance of our model ensembles at predicting increases in AGB is likely because forests follow relatively predictable growth curves (Jonsson et al., 2020; Luo et al., 2019; Repo et al., 2021). Gains in biomass are governed by tree physiology, climate, soils, and other site conditions (Jarvis & Linder, 2000; Jonsson et al., 2020) that constrain the minimum and maximum level of gain in any given time period. Previous studies have generally found stand age to be the best predictor of biomass growth (Jonsson et al., 2020; Luo et al., 2019). While stand age was included in the possible predictor variables, none of the models selected it, likely because it was only collected at ~20% of PSPs in our database. Instead of stand age, the models all selected initial stand biomass as the most important variable when predicting AGB change, with low initial biomass contributing to the largest modeled increases in predicted ΔAGB (Figure 5). Previous research on growth curves of boreal tree species shows that biomass is highly correlated with stand age (Jonsson et al., 2020; Repo et al., 2021), which means that the initial biomass is likely acting as a proxy for stand age.

Model predictions of AGB loss had much higher uncertainty than predictions of gain, correctly identifying losses in the fully withheld test set 41.5% and 60.2% of the time in the SWE and IWE models, respectively. In addition, the models' ability to predict AGB loss degraded more rapidly over time than AGB gain, with a rapid decline in accuracy at the 20-year prediction interval (Appendix S1: Figure S11a). In the boreal forest, loss of biomass is mostly driven by stand-replacing disturbances such as wildfire and logging (Wang et al., 2021; Wulder

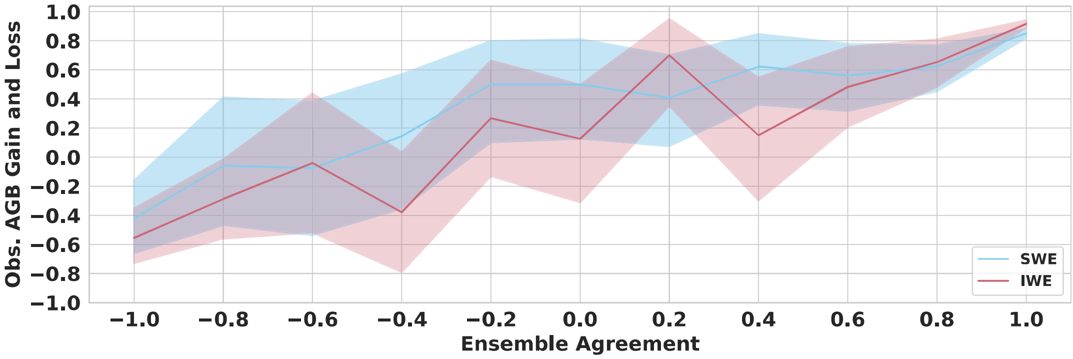

FIGURE 7 Model ensemble agreement. The ensemble agreement versus the mean (±99% CI) fraction of sites where loss or gain is observed in the test$_{ens}$ set for the site withholding ensemble (SWE) and the interval withholding ensemble (IWE). For ensemble agreement, 1 is equivalent to all 10 models predicting aboveground biomass (AGB) gain at a site and −1 is equivalent to all models predicting AGB loss. For observed gain and loss, 1 represents 100% of sites experiencing AGB gains while −1 represents 100% loss.

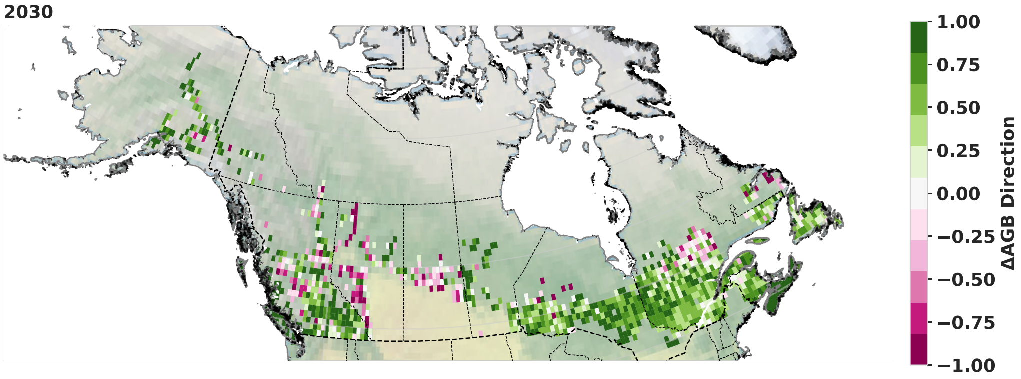

FIGURE 8 Future direction of change. The directional agreement of sites in a 1° × 1° box where the site withholding ensemble multi-model mean predicts an increase in aboveground biomass (AGB) to 2030. A value of 1 indicates all sites had predicted increases in AGB, whereas −1 indicates all sites had predicted decreases in AGB.

et al., 2020), which were both excluded from our modeling. Biomass loss due to nonstand-replacing disturbances is expected to be smaller in both spatial extent and magnitude (Sulla-Menashe et al., 2018), and was observed in 17.8% of sites in the PSP database. Biomass loss from nonstand-replacing disturbance is primarily driven by tree mortality from pests, pathogens, accumulated drought stress, and other tree-level factors (Hember et al., 2017b; Kautz et al., 2017; Rogers et al., 2018). In addition, AGB loss is less constrained because theoretically up to 100% of the trees within a stand could die in any given interval. This, along with the complexity of the drivers, makes AGB loss fundamentally more difficult to predict.

Recent studies have shown there are legacy effects and resilience debts that lead to nondisturbance-driven declines in AGB (Boyd et al., 2021; Itter et al., 2019), and that indicators of AGB loss can be detected in remotely sensed data as many as 24 years prior to the loss event (Rogers et al., 2018). Our results (Figure 6b,c) support these findings. However, the combined importance of EWS metrics was considerably less than that of survey and climate predictors but comparable to the combined importance of species data (Figure 4a). The highest ranked importance for remotely sensed EWS metrics (NDII and NDVI respectively) was only 14th in permutation importance (Appendix S1: Figure S5) and 11th in SHAP importance (Figure 5). Hence, although there is evidence that the temporal limitations for prediction are limited by the temporal coverage of data (see above), these lines of reasoning suggest ML model predictions of AGB change can be used up to roughly 25–30 years after the last observation of a site, but not longer, even given sufficient data availability. The conditional variance (ddj S2.t), a metric that is correlated with rapid state changes in ecological time series (Carpenter & Brock, 2011; Dakos et al., 2012, 2013), for both NDII and NDVI was negatively correlated with biomass changes. The fact that NDWI conditional variance shows an opposite relationship is unexpected and is perhaps indicative of locations that have more available water. The reason NDII pulse is negatively correlated with AGB change is not entirely clear; however, the magnitude of a vegetation pulse may be indicative of the degree to which a site is water limited, and previous research has shown that vegetation declines are more likely in the more water limited parts of the boreal forest (Berner & Goetz, 2022).

Improving performance with model ensembles

The limitations in any given single model's prediction of loss are offset considerably by using a multi-model ensemble. When there is high intra-ensemble agreement on biomass loss, the likelihood of loss being observed is high. Our results suggest that if all 10 ML models predict a decline in AGB, then a decline in biomass is expected with >70% probability. The multi-model mean also outperformed individual models, which improves our confidence in future predictions. The other advantage of using a *k*-fold model ensemble is that it allows for the quantification of uncertainties when performing forecasting through the use of ensemble means and model agreement metrics (James et al., 2013).

We tested two 10-member ensembles based on different withholding procedures: the SWE, where sites are strictly withheld in the test sets, and the IWE, where the model is allowed to train on a site at a different part of the time series (for sites with more than two measurements). The two withholding procedures provide different insights. The SWE models are applicable when applied to completely new sites, sites with only a single measurement, or as a potential foundation for developing gridded models. The IWE models are applicable for inventory sites with at least three repeated measurements, such as the majority of sites contained in our PSP database. The IWE models have higher overall performance, with an R^2 of 0.6 and significantly better ability to detect loss with a direction accuracy of 60.2% versus 41.5% for the SWE. SWE and IWE model performance is almost identical at sites with only two measurements (Figure 3b), which is expected since the IWE models are not allowed to train at those sites. For use cases in which predictions are only needed at existing PSPs, the IWE approach offers a substantial improvement in performance.

Modeling the future

In eastern Canada, as well as Alaska, our model ensemble overwhelmingly predicted increases in biomass, whereas the results are mixed in central and western Canada with large areas of predicted declines. Spatially, this is reasonably consistent with the long-term trends of both Landsat NDVI (Appendix S1: Figure S18) as well as observations of increasing tree mortality and limited biomass gains in the drier portions of southern Canadian boreal forests (Hember et al., 2017a, 2017b; Hogg et al., 2008; Peng et al., 2011). Although comparisons of our site-based predictions to existing gridded studies on biomass change are challenging, there are some relevant patterns. Multiple recent studies have shown that climate and climate change impacts differed among regions (Olsson et al., 2019), and that nondisturbance-driven trends in vegetation productivity are strongly influenced by water availability and temperature (Berner & Goetz, 2022; Buermann et al., 2013; Sulla-Menashe et al., 2018). The three most important climate variables were all climatology metrics with both TD (a.k.a. continentality) and mean summer precipitation (MSP) negatively associated with AGB change, and coldest monthly temperature positively associated with AGB change.

In most non-water-limited regions such as eastern Canada and parts of British Columbia, previous research has shown that warming temperatures are driving significant increases in vegetation productivity (Crous et al., 2022; D'Orangeville et al., 2016; Peng et al., 2011; Sulla-Menashe et al., 2018). This is consistent with both TD and the mean coldest month temperature (MCMT) predictors, as well as the positive association between AGB and frost-free period trend (the most important climate trend predictor). The relationship between ΔAGB and TD exhibits a clear threshold at $TD > 30°C$ (Appendix S1: Figure S6), which reflects the divide between maritime-influenced regions like British Columbia and interior boreal forest regions. The negative association between MSP and predicted AGB change is consistent with both the radiation limitation (e.g., cloudiness/rain during the growing season) and/or soil waterlogging, both of which are known to limit boreal AGB growth.

In contrast, over central and western Canada where our models predict more mixed AGB change, previous research has shown that warming has resulted in smaller trends and greater vulnerability to drought, especially in the warmest margins of both the boreal forest biome and its major forest types (Berner & Goetz, 2022; Girardin et al., 2016; Hember et al., 2017a; Peng et al., 2011; Sulla-Menashe et al., 2018). The regional differences between the response to warming can best be seen in the association between mean warmest month temperature (MWMT) trend and AGB change (Appendix S1: Figure S7), where the largest MWMT trends are associated with the largest increases and the largest decreases in AGB. Maps of the SHAP values of the five most important predictor variables as well as those variables discussed in this section are included in Appendix S1: Figures S19–S26. It should also be noted that the relative importance of climate variables increases considerably when we look at the subset of sites where we predict declines in AGB (Appendix S1: Figure S7). Taken together, these findings support our fourth hypothesis that the direction of future AGB change will vary regionally depending on climatology and climate trends. This is consistent with previous work (Berner & Goetz, 2022) and suggests that while climate change will have a positive impact on forest AGB in many regions, there are limitations of warming on increasing biomass as climate change continues and climate change will be a significant factor in nondisturbance-induced AGB declines.

Our ensemble predictions for ΔAGB out to 2025, 2030, and 2040 (Figure 8; Appendix S1: Figure S10) show similar spatial patterns to our predictions for 2020, with the fraction of sites predicted to increase from 77% in 2020 to almost 80% in 2040. This does not necessarily reflect biome-wide responses to climate change, and may partly reflect regional biases in PSP sampling. Currently, the number of sites with repeat measurements is heavily biased toward regions with active forestry (Wulder et al., 2020), with Nova Scotia and Quebec together accounting for more than 54% of all site measurements but only a small portion of the North American boreal forest area. Our results, as well as previous studies (D'Orangeville et al., 2016; Girardin et al., 2016; Hember et al., 2017b; Sulla-Menashe et al., 2018), strongly suggest these regions are not the ones currently experiencing biomass loss or likely to experience it in the future. Moreover, our models are not designed to predict acute disturbances such as wildfire, which are increasing across the domain (Hanes et al., 2018; Jain et al., 2022; Kasischke et al., 2010; Veraverbeke et al., 2017). Hence, the fact that >20% of sites are predicted to lose biomass even without acute disturbances is of concern, particularly given land surface models simulate an overwhelmingly positive influence of climate change on North American boreal forests (Friend et al., 2014; Olsson et al., 2019; Wang et al., 2021).

Our ML-based modeling approach offers an excellent complement to existing modeling methodologies. High spatial resolution process-based models can be applied across the regions, but are limited in terms of the locality (time/space) at which they can predict forest change, that is, a model that works well for one site might not translate well to another.

Our ML-based modeling approach offers an excellent complement to existing modeling methodologies. High spatial resolution process-based models can be applied across regions (e.g., Foster et al., 2019, 2022) and compared with our data-constrained approach. At larger scales, the process-based models used in climate models are designed to predict longer term dynamics and are not explicitly intended for forecasting short-term trends at site-specific locations. In contrast, our ML-based methodology can incorporate very local-scale (i.e., <1 km) effects and observed responses that are harder for these process-based models to capture. However, process-based models have a definitive advantage in being able to mechanistically represent nonlinear dynamics such as fire disturbance, and can provide insight into how forests may change under completely novel conditions (i.e., conditions that the data used to train ML models have not seen at all) (Foster et al., 2022). Further research combining these different approaches, for example, model-data hybrid approaches and data assimilation, may provide greater insight into the impacts of climate change on boreal forest demographics. In addition, comparing future predictions from our modeling to future observations may allow for the identification of ecosystem state transitions and tipping points.

Our study was only possible because of the long-term devoted sampling and archiving of forest inventory plots across government agencies in Canada and Alaska. This speaks to the power of long-term repeat measurements, as changes in forest demographics are only detectable using multiple observations over many years. As such, we argue there are substantial benefits to the scientific and management communities of continued and expanded PSPs. Even so, these data do not come without limitations, for example, we noted large geographic bias in PSP density across boreal North America. Moreover, there are very little field data from Alaska and, more broadly, from the northern parts of boreal forest outside of areas with commercial forestry. AGB data from repeat lidar and/or synthetic aperture radar could fill this gap, but more work is needed to compare the accuracy of field and remotely sensed AGB estimates. There are also differences in sampling methods between regions, with many sites missing potentially important predictors such as stand age, and significant differences in the dbh thresholds for what counts as a "tree." As such, future sampling designs might consider comparable protocols to facilitate assessments of climate change on boreal forests. Related, we encourage an increased focus on regional intercomparisons when designing sampling methodologies.

CONCLUSION

Climate change is driving significant changes in North American boreal forests. The ability to predict changes in AGB is essential for multiple communities ranging from resource managers to Earth system modelers. We demonstrate that when ML algorithms are informed with rich PSP data, they are able to predict AGB changes up to 30 years into the future. Moreover, by training on sites across the entire domain, we were able to accurately predict changes in AGB even in regions with a lack of PSP data. As expected, AGB loss was more challenging to predict than AGB gains, but the greater importance of climate variables for predicting declining biomass suggests climate change will have a significant role in driving nondisturbance-induced biomass loss. Limitations in predicting AGB losses can be partially offset by increasing the number of measurements at PSP sites and using a multi-model ensemble. This work also lays the foundation for developing ML-based gridded models and regional products that could be used for management, vulnerability analyses, regional planning, model intercomparisons, general scientific understanding, and informing process-based modeling.

AUTHOR CONTRIBUTIONS

Sol Cooperdock and Brendan Rogers conceived the study. Sol Cooperdock curated the data with some processing done by Logan T. Berner. Arden L. Burrell developed the method with input from Brendan Rogers and Sol Cooperdock. Arden L. Burrell performed the analysis and wrote the manuscript. Sol Cooperdock, Stefano Potter, Logan T. Berner, Robert Hember, Matthew J. Macander, Xanthe J. Walker, Richard Massey, Adrianna C. Foster, Michelle C. Mack, Scott J. Goetz, and Brendan Rogers reviewed and provided feedback on the manuscript.

ACKNOWLEDGMENTS

This work was funded by the National Aeronautics and Space Administration (NASA) Arctic-Boreal Vulnerability Experiment (ABoVE) grants NNX17AE44G and 80NSCS 19M01 and the Department of Defense Strategic Environmental Research and Development Program (SERDP) contract RC18-1183. We thank the workforce involved in planning, collecting, and managing forest inventories, as well as access to the inventory data, including the Cooperative Alaska Forest Inventory program run by the United States Department of Agriculture Forest Service and Canadian Provincial agencies, including the British Columbia Ministry of Forests, Lands, Natural Resource Operations and Rural Development, Alberta Agriculture and Forestry, Saskatchewan Ministry of Environment Forest Service, Manitoba Conservation and Water Stewardship, Government of the Northwest Territories Department of Environment and Natural Resources, Government of Yukon Forest Management Branch, Ontario Ministry of Natural Resources and Forestry, Ministére des ressources naturelles du Québec, Nova Scotia Department of Natural Resources, New Brunswick Department of Energy and Resource Development, and the Newfoundland and Labrador Department of Fisheries, Forestry, and Agriculture. We also thank the NVIDA Academic Hardware Grant for providing the hardware used in this analysis.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

No new data were collected for this study. Eighteen existing datasets were used, nine of which are already published and available. A complete list of publicly available datasets used for this manuscript can be found in Appendix S1: Tables S5 and S6. Nine of the datasets are available from Canadian Provincial governments with restrictions, including licensing and nondisclosure agreements, and are not accessible to the public. The datasets and relevant government agencies are described in Appendix S1: Table S6. The code used in this analysis (Burrell, 2023) is available from Zenodo: https://doi.org/10.5281/zenodo.10234140.

ORCID

Arden L. Burrell https://orcid.org/0000-0001-8762-1296
Stefano Potter https://orcid.org/0000-0002-5141-3409
Logan T. Berner https://orcid.org/0000-0001-8947-0479
Matthew J. Macander https://orcid.org/0000-0003-2808-208X
Xanthe J. Walker https://orcid.org/0000-0002-2448-691X
Adrianna C. Foster https://orcid.org/0000-0002-7382-0013
Michelle C. Mack https://orcid.org/0000-0003-1279-4242
Scott J. Goetz https://orcid.org/0000-0002-6326-4308
Brendan Rogers https://orcid.org/0000-0001-6711-8466

REFERENCES

Abatzoglou, J. T., A. P. Williams, L. Boschetti, M. Zubkova, and C. A. Kolden. 2018. "Global Patterns of Interannual Climate–Fire Relationships." *Global Change Biology* 24: 5164–75. https://doi.org/10.1111/gcb.14405.

Alexander, H. D., M. C. Mack, S. Goetz, P. S. A. Beck, and E. F. Belshe. 2012. "Implications of Increased Deciduous Cover on Stand Structure and Aboveground Carbon Pools of Alaskan Boreal Forests." *Ecosphere* 3: art45. https://doi.org/10.1890/ES11-00364.1.

ALRahahleh, L., A. Kilpeläinen, V.-P. Ikonen, H. Strandman, A. Venäläinen, and H. Peltola. 2018. "Effects of CMIP5 Projections on Volume Growth, Carbon Stock and Timber Yield in Managed Scots Pine, Norway Spruce and Silver Birch Stands under Southern and Northern Boreal Conditions." *Forests* 9: 208. https://doi.org/10.3390/f9040208.

Anderegg, L. D. L., D. M. Griffith, J. Cavender-Bares, W. J. Riley, J. A. Berry, T. E. Dawson, and C. J. Still. 2021. "Representing Plant Diversity in Land Models: An Evolutionary Approach to Make 'Functional Types' More Functional." *Global Change Biology* 28: 2541–54. https://doi.org/10.1111/gcb.16040.

Anderegg, W. R. L., A. T. Trugman, G. Badgley, C. M. Anderson, A. Bartuska, P. Ciais, D. Cullenward, et al. 2020. "Climate-Driven Risks to the Climate Mitigation Potential of Forests." *Science* 368: eaaz7005. https://doi.org/10.1126/science.aaz7005.

Baltzer, J. L., N. J. Day, X. J. Walker, D. Greene, M. C. Mack, H. D. Alexander, D. Arseneault, et al. 2021. "Increasing Fire and the Decline of Fire Adapted Black Spruce in the Boreal Forest." *Proceedings of the National Academy of Sciences of the United States of America* 118: e2024872118. https://doi.org/10.1073/pnas.2024872118.

Berner, L. T., and S. J. Goetz. 2022. "Satellite Observations Document Trends Consistent with a Boreal Forest Biome Shift." *Global Change Biology* 28: 3275–92. https://doi.org/10.1111/gcb.16121.

Berner, L. T., R. Massey, P. Jantz, B. C. Forbes, M. Macias-Fauria, I. Myers-Smith, T. Kumpula, et al. 2020. "Summer Warming Explains Widespread but Not Uniform Greening in the Arctic Tundra Biome." *Nature Communications* 11: 4621. https://doi.org/10.1038/s41467-020-18479-5.

Birch, L., C. R. Schwalm, S. Natali, D. Lombardozzi, G. Keppel-Aleks, J. Watts, X. Lin, et al. 2021. "Addressing Biases in Arctic–Boreal Carbon Cycling in the Community Land Model Version 5." *Geoscientific Model Development* 14: 3361–82. https://doi.org/10.5194/gmd-14-3361-2021.

Boussetta, S., G. Balsamo, A. Beljaars, A.-A. Panareda, J.-C. Calvet, C. Jacobs, B. van den Hurk, et al. 2013. "Natural Land Carbon Dioxide Exchanges in the ECMWF Integrated Forecasting System: Implementation and Offline Validation." *Journal of Geophysical Research: Atmospheres* 118: 5923–46. https://doi.org/10.1002/jgrd.50488.

Boyd, M. A., L. T. Berner, P. Doak, S. J. Goetz, B. M. Rogers, D. Wagner, X. J. Walker, and M. C. Mack. 2019. "Impacts of Climate and Insect Herbivory on Productivity and Physiology of Trembling Aspen (*Populus tremuloides*) in Alaskan Boreal Forests." *Environmental Research Letters* 14: 085010. https://doi.org/10.1088/1748-9326/ab215f.

Boyd, M. A., L. T. Berner, A. C. Foster, S. J. Goetz, B. M. Rogers, X. J. Walker, and M. C. Mack. 2021. "Historic Declines in Growth Portend Trembling Aspen Death during a Contemporary Leaf Miner Outbreak in Alaska." *Ecosphere* 12: e03569. https://doi.org/10.1002/ecs2.3569.

Bradshaw, C. J. A., and I. G. Warkentin. 2015. "Global Estimates of Boreal Forest Carbon Stocks and Flux." *Global and Planetary Change* 128: 24–30. https://doi.org/10.1016/j.gloplacha.2015.02.004.

Buermann, W., P. R. Bikash, M. Jung, D. H. Burn, and M. Reichstein. 2013. "Earlier Springs Decrease Peak Summer Productivity in North American Boreal Forests." *Environmental Research Letters* 8: 024027. https://doi.org/10.1088/1748-9326/8/2/024027.

Burke, E., Y. Zhang, and G. Krinner. 2020. "Evaluating Permafrost Physics in the CMIP6 Models and Their Sensitivity to Climate Change." https://doi.org/10.5194/tc-2019-309.

Burrell, A. L. 2023. "ArdenB/BorealRF: Final (v1.0). Code." Zenodo. https://doi.org/10.5281/zenodo.10234140.

Burrell, A. L., E. A. Kukavskaya, R. Baxter, Q. Sun, and K. Barrett. 2021. "Post-Fire Recruitment Failure as a Driver of Forest to Non-Forest Ecosystem Shifts in Boreal Regions." In *Ecosystem Collapse and Climate Change, Ecological Studies*, edited by J. Canadell and R. Jackson, 69–100. Cham: Springer International Publishing.

Carpenter, S. R., and W. A. Brock. 2011. "Early Warnings of Unknown Nonlinear Shifts: A Nonparametric Approach." *Ecology* 92: 2196–2201. https://doi.org/10.1890/11-0716.1.

Chen, H. Y. H., Y. Luo, P. B. Reich, E. B. Searle, and S. R. Biswas. 2016. "Climate Change-Associated Trends in Net Biomass Change Are Age Dependent in Western Boreal Forests of Canada." *Ecology Letters* 19: 1150–58. https://doi.org/10.1111/ele.12653.

Chen, T., and C. Guestrin. 2016. "XGBoost: A Scalable Tree Boosting System." In *Proceedings of 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. https://doi.org/10.1145/2939672.2939785.

Colwell, R. K., A. Chao, N. J. Gotelli, S.-Y. Lin, C. X. Mao, R. L. Chazdon, and J. T. Longino. 2012. "Models and Estimators Linking Individual-Based and Sample-Based Rarefaction, Extrapolation and Comparison of Assemblages." *Journal of Plant Ecology* 5: 3–21. https://doi.org/10.1093/jpe/rtr044.

Crous, K. Y., J. Uddling, and M. G. De Kauwe. 2022. "Temperature Responses of Photosynthesis and Respiration in Evergreen Trees from Boreal to Tropical Latitudes." *New Phytologist* 234: 353–374. https://doi.org/10.1111/nph.17951.

Dakos, V., S. R. Carpenter, W. A. Brock, A. M. Ellison, V. Guttal, A. R. Ives, S. Kéfi, et al. 2012. "Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS One* 7: e41010. https://doi.org/10.1371/journal.pone.0041010.

Dakos, V., T. C. Carpenter, L. Lahti, and M. V. Dakos. 2013. "Package Earlywarnings."

Di Lucca, C. M. 2019. "Using the Tree and Stand Simulator (TASS) Model to Predict the Effect of Stand Management on Quantity and Value of Carbon and Biomass in British Columbia, Canada." https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/forestry/stewardship/forest-analysis-inventory/growth-yield/iufro_2019_poster_presentation_mariodilucca.pdf.

D'Orangeville, L., L. Duchesne, D. Houle, D. Kneeshaw, B. Côté, and N. Pederson. 2016. "Northeastern North America as a Potential Refugium for Boreal Forests in a Warming Climate." *Science* 352: 1452–55. https://doi.org/10.1126/science.aaf4951.

D'Orangeville, L., D. Houle, L. Duchesne, R. P. Phillips, Y. Bergeron, and D. Kneeshaw. 2018. "Beneficial Effects of Climate Warming on Boreal Tree Growth May be Transitory." *Nature Communications* 9: 3213. https://doi.org/10.1038/s41467-018-05705-4.

Felton, A. J. 2021. "Chapter 5 – Response of Terrestrial Net Primary Productivity to Precipitation Extremes: Patterns, Mechanisms, and Uncertainties." In *Climate Change and Extreme Events*, edited by A. Fares, 57–81. Amsterdam: Elsevier. https://doi.org/10.1016/B978-0-12-822700-8.00010-X.

Foster, A. C., A. H. Armstrong, J. K. Shuman, H. H. Shugart, B. M. Rogers, M. C. Mack, S. J. Goetz, and K. J. Ranson. 2019. "Importance of Tree- and Species-Level Interactions with Wildfire, Climate, and Soils in Interior Alaska: Implications for Forest Change under a Warming Climate." *Ecological Modelling* 409: 108765. https://doi.org/10.1016/j.ecolmodel.2019.108765.

Foster, A. C., J. K. Shuman, B. M. Rogers, X. J. Walker, M. C. Mack, L. L. Bourgeau-Chavez, S. Veraverbeke, and S. J. Goetz. 2022. "Bottom-up Drivers of Future Fire Regimes in Western Boreal North America." *Environmental Research Letters* 17: 025006. https://doi.org/10.1088/1748-9326/ac4c1e.

Friend, A. D., W. Lucht, T. T. Rademacher, R. Keribin, R. Betts, P. Cadule, P. Ciais, et al. 2014. "Carbon Residence Time Dominates Uncertainty in Terrestrial Vegetation Responses to Future Climate and Atmospheric CO_2." *Proceedings of the National Academy of Sciences of the United States of America* 111: 3280–85. https://doi.org/10.1073/pnas.1222477110.

Gauthier, S., P. Bernier, T. Kuuluvainen, A. Z. Shvidenko, and D. G. Schepaschenko. 2015. "Boreal Forest Health and Global Change." *Science* 349: 819–822. https://doi.org/10.1126/science.aaa9092.

Girardin, M. P., O. Bouriaud, E. H. Hogg, W. Kurz, N. E. Zimmermann, J. M. Metsaranta, R. de Jong, et al. 2016. "No Growth Stimulation of Canada's Boreal Forest under Half-Century of Combined Warming and CO_2 Fertilization." *Proceedings of the National Academy of Sciences of the United States of America* 113: E8406–E8414. https://doi.org/10.1073/pnas.1610156113.

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore. 2017. "Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone." *Remote Sensing of Environment* 202: 18–27. https://doi.org/10.1016/j.rse.2017.06.031.

Gruber, S. 2012. "Derivation and Analysis of a High-Resolution Estimate of Globalpermafrost Zonation." *The Cryosphere* 6: 221–233. https://doi.org/10.5194/tc-6-221-2012.

Guay, K. C., P. S. A. Beck, L. T. Berner, S. J. Goetz, A. Baccini, and W. Buermann. 2014. "Vegetation Productivity Patterns at High Northern Latitudes: A Multi-Sensor Satellite Data Assessment." *Global Change Biology* 20: 3147–58. https://doi.org/10.1111/gcb.12647.

Guo, W., H. Liu, and X. Wu. 2018. "Vegetation Greening despite Weakening Coupling between Vegetation Growth and Temperature over the Boreal Region." *Journal of Geophysical Research: Biogeosciences* 123: 2376–87. https://doi.org/10.1029/2018JG004486.

Hanes, C. C., X. Wang, P. Jain, M.-A. Parisien, J. M. Little, and M. D. Flannigan. 2018. "Fire-Regime Changes in Canada over the Last Half Century." *Canadian Journal of Forest Research* 49: 256–269. https://doi.org/10.1139/cjfr-2018-0293.

Hember, R. A., W. A. Kurz, and N. C. Coops. 2017a. "Increasing Net Ecosystem Biomass Production of Canada's Boreal and Temperate Forests despite Decline in Dry Climates." *Global Biogeochemical Cycles* 31: 134–158. https://doi.org/10.1002/2016GB005459.

Hember, R. A., W. A. Kurz, and N. C. Coops. 2017b. "Relationships between Individual-Tree Mortality and Water-Balance Variables Indicate Positive Trends in Water Stress-Induced Tree Mortality across North America." *Global Change Biology* 23: 1691–1710. https://doi.org/10.1111/gcb.13428.

Hengl, T., J. M. de Jesus, G. B. M. Heuvelink, M. R. Gonzalez, M. Kilibarda, A. Blagotić, W. Shangguan, et al. 2017. "SoilGrids250m: Global Gridded Soil Information Based on Machine Learning." *PLoS One* 12: e0169748. https://doi.org/10.1371/journal.pone.0169748.

Hogg, E. H. (T.)., J. P. Brandt, and M. Michaelian. 2008. "Impacts of a Regional Drought on the Productivity, Dieback, and Biomass of Western Canadian Aspen Forests." *Canadian Journal of Forest Research* 38: 1373–84. https://doi.org/10.1139/X08-001.

Itter, M. S., L. D'Orangeville, A. Dawson, D. Kneeshaw, L. Duchesne, and A. O. Finley. 2019. "Boreal Tree Growth Exhibits Decadal-Scale Ecological Memory to Drought and Insect Defoliation, but No Negative Response to Their Interaction." *Journal of Ecology* 107: 1288–1301. https://doi.org/10.1111/1365-2745.13087.

Jain, P., D. Castellanos-Acuna, S. C. P. Coogan, J. T. Abatzoglou, and M. D. Flannigan. 2022. "Observed Increases in Extreme Fire Weather Driven by Atmospheric Humidity and Temperature." *Nature Climate Change* 12: 63–70. https://doi.org/10.1038/s41558-021-01224-1.

James, G., D. Witten, T. Hastie, and R. Tibshirani. 2013. "Resampling Methods." In *An Introduction to Statistical Learning: With Applications in R*, Springer Texts in Statistics., edited by G. James, D. Witten, T. Hastie, and R. Tibshirani, 175–201. New York, NY: Springer. https://doi.org/10.1007/978-1-4614-7138-7_5.

Jarvis, P., and S. Linder. 2000. "Constraints to Growth of Boreal Forests." *Nature* 405: 904–5. https://doi.org/10.1038/35016154.

Jia, G., E. Shevliakova, P. Artaxo, D. Noblet-Ducoudré, R. Houghton, J. House, K. Kitajima, C. Lennard, A. Popp, and A. Sirin. 2019. "Chapter 2: Land-Climate Interactions." In: *IPCC. Climate Change and Land: A Special Report of the Intergovernmental Panel on Climate Change*, 131–247.

Jones, D. T. 2019. "Setting the Standards for Machine Learning in Biology." *Nature Reviews. Molecular Cell Biology* 20: 659–660. https://doi.org/10.1038/s41580-019-0176-5.

Jonsson, M., J. Bengtsson, J. Moen, L. Gamfeldt, and T. Snäll. 2020. "Stand Age and Climate Influence Forest Ecosystem Service Delivery and Multifunctionality." *Environmental Research Letters* 15: 0940a8. https://doi.org/10.1088/1748-9326/abaf1c.

Kasischke, E. S., D. L. Verbyla, T. S. Rupp, A. D. McGuire, K. A. Murphy, R. Jandt, J. L. Barnes, et al. 2010. "Alaska's Changing Fire Regime—Implications for the Vulnerability of Its Boreal Forests." *Canadian Journal of Forest Research* 40: 1313–24. https://doi.org/10.1139/X10-098.

Kasischke, E. S., D. Williams, and D. Barry. 2002. "Analysis of the Patterns of Large Fires in the Boreal Forest Region of Alaska." *International Journal of Wildland Fire* 11: 131–144. https://doi.org/10.1071/wf02023.

Kaufman, S., S. Rosset, C. Perlich, and O. Stitelman. 2012. "Leakage in Data Mining: Formulation, Detection, and Avoidance." *ACM Transactions on Knowledge Discovery from Data* 6: 15: 1–15:21. https://doi.org/10.1145/2382577.2382579.

Kautz, M., A. J. H. Meddens, R. J. Hall, and A. Arneth. 2017. "Biotic Disturbances in Northern Hemisphere Forests – A Synthesis of Recent Data, Uncertainties and Implications for Forest Monitoring and Modelling." *Global Ecology and Biogeography* 26: 533–552. https://doi.org/10.1111/geb.12558.

Kolby Smith, W., S. C. Reed, C. C. Cleveland, A. P. Ballantyne, W. R. L. Anderegg, W. R. Wieder, Y. Y. Liu, and S. W.

Running. 2016. “Large Divergence of Satellite and Earth System Model Estimates of Global Terrestrial CO_2 Fertilization.” *Nature Climate Change* 6: 306–310. https://doi.org/10.1038/nclimate2879.

Lidberg, W., M. Nilsson, and A. Ågren. 2020. “Using Machine Learning to Generate High-Resolution Wet Area Maps for Planning Forest Management: A Study in a Boreal Forest Landscape.” *Ambio* 49: 475–486. https://doi.org/10.1007/s13280-019-01196-9.

Liu, L., L. Gudmundsson, M. Hauser, D. Qin, S. Li, and S. I. Seneviratne. 2020. “Soil Moisture Dominates Dryness Stress on Ecosystem Production Globally.” *Nature Communications* 11: 4892. https://doi.org/10.1038/s41467-020-18631-1.

Liu, Y. Y., A. I. J. M. van Dijk, R. A. M. de Jeu, J. G. Canadell, M. F. McCabe, J. P. Evans, and G. Wang. 2015. “Recent Reversal in Loss of Global Terrestrial Biomass.” *Nature Climate Change* 5: 470–74. https://doi.org/10.1038/nclimate2581.

Liu, Z., C. Peng, T. Work, J.-N. Candau, A. DesRochers, and D. Kneeshaw. 2018. “Application of Machine-Learning Methods in Forest Ecology: Recent Progress and Future Challenges.” *Environmental Reviews* 26: 339–350. https://doi.org/10.1139/er-2018-0034.

Lloyd, A. H., and A. G. Bunn. 2007. “Responses of the Circumpolar Boreal Forest to 20th Century Climate Variability.” *Environmental Research Letters* 2: 045013. https://doi.org/10.1088/1748-9326/2/4/045013.

Lundberg, S. M., and S.-I. Lee. 2017. “A Unified Approach to Interpreting Model Predictions.” In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, 4768–4777.

Luo, Y., H. Y. H. Chen, E. J. B. McIntire, and D. W. Andison. 2019. “Divergent Temporal Trends of Net Biomass Change in Western Canadian Boreal Forests.” *Journal of Ecology* 107: 69–78. https://doi.org/10.1111/1365-2745.13033.

Mekonnen, Z. A., W. J. Riley, J. T. Randerson, R. F. Grant, and B. M. Rogers. 2019. “Expansion of High-Latitude Deciduous Forests Driven by Interactions between Climate Warming and Fire.” *Nature Plants* 5: 952–58. https://doi.org/10.1038/s41477-019-0495-8.

Meyer, H., and E. Pebesma. 2021. “Predicting into Unknown Space? Estimating the Area of Applicability of Spatial Prediction Models.” *Methods in Ecology and Evolution* 12: 1620–33. https://doi.org/10.1111/2041-210X.13650.

Obu, J., S. Westermann, A. Bartsch, N. Berdnikov, H. H. Christiansen, A. Dashtseren, R. Delaloye, et al. 2019. “Northern Hemisphere Permafrost Map Based on TTOP Modelling for 2000–2016 at 1 km^2 Scale.” *Earth Science Reviews* 193: 299–316. https://doi.org/10.1016/j.earscirev.2019.04.023.

Olsson, L., H. Barbosa, S. Bhadwal, A. Cowie, K. Delusca, D. Flores-Renteria, K. Hermans, E. Jobbagy, W. Kurz, and D. Li. 2019. “Chapter 4: Land Degradation.” In *IPCC. Climate and Change and Land: A Special Report of the Intergovernmental Panel on Climate Change.*

Pan, Y., R. A. Birdsey, J. Fang, R. Houghton, P. E. Kauppi, W. A. Kurz, O. L. Phillips, et al. 2011. “A Large and Persistent Carbon Sink in the World’s Forests.” *Science* 333: 988–993. https://doi.org/10.1126/science.1201609.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, et al. 2011. “Scikit-Learn: Machine Learning in Python.” *Journal of Machine Learning Research* 12: 2825–30.

Peng, C., Z. Ma, X. Lei, Q. Zhu, H. Chen, W. Wang, S. Liu, W. Li, X. Fang, and X. Zhou. 2011. “A Drought-Induced Pervasive Increase in Tree Mortality across Canada’s Boreal Forests.” *Nature Climate Change* 1: 467–471. https://doi.org/10.1038/nclimate1293.

Repo, A., T. Rajala, H. M. Henttonen, A. Lehtonen, M. Peltoniemi, and J. Heikkinen. 2021. “Age-Dependence of Stand Biomass in Managed Boreal Forests Based on the Finnish National Forest Inventory Data.” *Forest Ecology and Management* 498: 119507. https://doi.org/10.1016/j.foreco.2021.119507.

Rogers, B. M., K. Solvik, E. H. Hogg, J. Ju, J. G. Masek, M. Michaelian, L. T. Berner, and S. J. Goetz. 2018. “Detecting Early Warning Signals of Tree Mortality in Boreal North America Using Multiscale Satellite Data.” *Global Change Biology* 24: 2284–2304. https://doi.org/10.1111/gcb.14107.

Rusdah, D. A., and H. Murfi. 2020. “XGBoost in Handling Missing Values for Life Insurance Risk Prediction.” *SN Applied Sciences* 2: 1336. https://doi.org/10.1007/s42452-020-3128-y.

Sanderson, B. M., and R. A. Fisher. 2020. “Afiery Wake-Up Call for Climate Science.” *Nature Climate Change* 10: 175–77. https://doi.org/10.1038/s41558-020-0707-2.

Stocks, B. J., J. A. Mason, J. B. Todd, E. M. Bosch, B. M. Wotton, B. D. Amiro, M. D. Flannigan, et al. 2002. “Large Forest Fires in Canada, 1959–1997.” *Journal of Geophysical Research: Atmospheres* 107: FFR 5-1–FFR 5-12. https://doi.org/10.1029/2001JD000484.

Sulla-Menashe, D., C. E. Woodcock, and M. A. Friedl. 2018. “Canadian Boreal Forest Greening and Browning Trends: An Analysis of Biogeographic Patterns and the Relative Roles of Disturbance versus Climate Drivers.” *Environmental Research Letters* 13: 014007. https://doi.org/10.1088/1748-9326/aa9b88.

Sun, Q., A. Burrell, K. Barrett, E. Kukavskaya, L. Buryak, J. Kaduk, and R. Baxter. 2021. “Climate Variability May Delay Post-Fire Recovery of Boreal Forest in Southern Siberia, Russia.” *Remote Sensing* 13: 2247. https://doi.org/10.3390/rs13122247.

Theil, H. 1950. “A Rank-Invariant Method of Linear and Polynomial Regression Analysis, Part 3.” Presented at the Proceedings of Koninalijke Nederlandse Akademie van Weinenschatpen A, 1397–1412.

Trugman, A. T., N. J. Fenton, Y. Bergeron, X. Xu, L. R. Welp, and D. Medvigy. 2016. “Climate, Soil Organic Layer, and Nitrogen Jointly Drive Forest Development after Fire in the North American Boreal Zone.” *Journal of Advances in Modeling Earth Systems* 8: 1180–1209. https://doi.org/10.1002/2015MS000576.

Ung, C. -H., P. Bernier, and X. -J. Guo. 2008. “Canadian National Biomass Equations: New Parameter Estimates that Include British Columbia Data.” *Canadian Journal of Forest Research* 38: 1123–32. https://doi.org/10.1139/X07-224.

Veraverbeke, S., B. M. Rogers, M. L. Goulden, R. R. Jandt, C. E. Miller, E. B. Wiggins, and J. T. Randerson. 2017. “Lightning as a Major Driver of Recent Large Fire Years in North American Boreal Forests.” *Nature Climate Change* 7: 529–534. https://doi.org/10.1038/nclimate3329.

Walker, X. J., J. L. Baltzer, S. G. Cumming, N. J. Day, C. Ebert, S. Goetz, J. F. Johnstone, et al. 2019. “Increasing Wildfires Threaten Historic Carbon Sink of Boreal Forest

Soils." *Nature* 572: 520–23. https://doi.org/10.1038/s41586-019-1474-y.

Wang, J. A., A. Baccini, M. Farina, J. T. Randerson, and M. A. Friedl. 2021. "Disturbance Suppresses the Aboveground Carbon Sink in North American Boreal Forests." *Nature Climate Change* 11: 435–441. https://doi.org/10.1038/s41558-021-01027-4.

Wang, J. A., and M. A. Friedl. 2019. "The Role of Land Cover Change in Arctic-Boreal Greening and Browning Trends." *Environmental Research Letters* 14: 125007. https://doi.org/10.1088/1748-9326/ab5429.

Wang, T., A. Hamann, D. Spittlehouse, and C. Carroll. 2016. "Locally Downscaled and Spatially Customizable Climate Data for Historical and Future Periods for North America." *PLoS One* 11: e0156720. https://doi.org/10.1371/journal.pone.0156720.

Wulder, M. A., T. Hermosilla, J. C. White, and N. C. Coops. 2020. "Biomass Status and Dynamics over Canada's Forests: Disentangling Disturbed Area from Associated Aboveground Biomass Consequences." *Environmental Research Letters* 15: 094093. https://doi.org/10.1088/1748-9326/ab8b11.

Xia, Y., C. Liu, Y. Li, and N. Liu. 2017. "A Boosted Decision Tree Approach Using Bayesian Hyper-Parameter Optimization for Credit Scoring." *Expert Systems with Applications* 78: 225–241. https://doi.org/10.1016/j.eswa.2017.02.017.

Yang, C.-E., J. Mao, F. M. Hoffman, D. M. Ricciuto, J. S. Fu, C. D. Jones, and M. Thurner. 2018. "Uncertainty Quantification of Extratropical Forest Biomass in CMIP5 Models over the Northern Hemisphere." *Scientific Reports* 8: 10962. https://doi.org/10.1038/s41598-018-29227-7.

Yu, T., and H. Zhu. 2020. "Hyper-Parameter Optimization: A Review of Algorithms and Applications." https://doi.org/10.48550/arXiv.2003.05689.

Zhang, Y., N. C. Parazoo, A. P. Williams, S. Zhou, and P. Gentine. 2020. "Large and Projected Strengthening Moisture Limitation on End-of-Season Photosynthesis." *Proceedings of the National Academy of Sciences of the United States of America* 117: 9216–22. https://doi.org/10.1073/pnas.1914436117.

Zhang, Y., S. Piao, Y. Sun, B. M. Rogers, X. Li, X. Lian, Z. Liu, A. Chen, and J. Peñuelas. 2022. "Future Reversal of Warming-Enhanced Vegetation Productivity in the Northern Hemisphere." *Nature Climate Change* 12: 581–86. https://doi.org/10.1038/s41558-022-01374-w.

Zhu, P., Q. Zhuang, L. Welp, P. Ciais, M. Heimann, B. Peng, W. Li, C. Bernacchi, C. Roedenbeck, and T. F. Keenan. 2019. "Recent Warming Has Resulted in Smaller Gains in Net Carbon Uptake in Northern High Latitudes." *Journal of Climate* 32: 5849–63. https://doi.org/10.1175/JCLI-D-18-0653.1.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Burrell, Arden L., Sol Cooperdock, Stefano Potter, Logan T. Berner, Robert Hember, Matthew J. Macander, Xanthe J. Walker, et al. 2024. "The Predictability of Near-Term Forest Biomass Change in Boreal North America." *Ecosphere* 15(1): e4737. https://doi.org/10.1002/ecs2.4737